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ORIGINAL PAPER

An integrated method for matching forest machinery and a weight-value adjustment

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Abstract: Proper matching of forestry machinery is important when raising mechanization levels for forestry production. In the matching process, forestry machinery needs not only expertise, but also improved methods for solving problems. I propose combination of case-based reasoning (CBR) and rule-based reasoning (RBR) by calculating the similarity of quantitative parameters of various forestry machines in an analytical and hierarchical process. I calculated the similarity of machinery used in forest industries to enable better selection and matching of equipment. I propose a weight-value adjusting method based on sums of squares of deviations in which the individual parameter weights were modified in the process of application. During the process of system design, I put forward a design method knowledge base and generated a dynamic web reasoning framework to integrate the processes of forest industry machinery selection and weight-value adjustment. This enables expansion of the scope of the complete system and enhancement of the reasoning efficiency. I demonstrate the validity and practicability of this method using a practical example.

Keywords: forest industry, machinery selection and matching, weight-value determination, reasoning process, integration method

Introduction

China is a large producer of forest products. The levels of forest industry production and mechanization are in the forefront of the world. Although much forestry machinery has been created (Xiang 2003; Huang 2004; Shen 2005), mechanization of forest industries is still low in China in comparison levels in industrially developed countries. Further development of machinery and mechanized production should be promoted in the production of forest products in China.

Classification of forestry and woodworking machines in China has been proposed (Ma 2009). This method divides forestry and woodworking machines into three industries: (1) artificial board; (2) furniture; and (3) timber production. The low levels of mechanization in forest plantation management and timber production in China have resulted in low productivity levels. This has seriously restricted the efficiency of forest production. To enhance mechanized production, guidance is needed in the selection and matching of forestry machinery, and in mechanical maintenance. As various types of forestry production machinery are adapted to different production environments, it is necessary to match the characteristics of machines with their intended production environments to maximize results. In order to speed up the process of forestry mechanization in China, the demands of using scientific management theory and forestry mechanization technology in actual forestry production are becoming more and more pressing. During the promotion, the consultation and guidance from specialists are needed. And the specialists of forestry machinery selecting and matching can give guidance in this case.

The first expert system, DENDRL, in 1965 (Massart and Meuter 2008) has been widely used in mechanical maintenance, mechanical matches, mechanical fault diagnosis, and mechanical design (Aamodt and Plaza 1994; Chang and Joo 2006; Chang et al. 2008; Tsai and Chiu 2007). Rule-based reasoning (RBR) and case-based reasoning (CBR) are techniques in expert systems. RBR uses induction rules to determine, if a new problem should be inspected further. Based on similarity matching, CBR finds the case that is most similar to the new problem (Chou 2009). The core of CBR is to solve the new problem by reusing previous cases to improve reasoning efficiency. The reasoning process of CBR includes the following steps: retrieve, reuse, revise and retain. Retrieving locates similar previous cases from a Base Case. Reusing infers a proper solution to the current problem by

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reusing similar previous cases. Revising is to put forward solutions where necessary. Retrieving is the most important step in CBR. By retrieving from a base case, the new situation (new case) and the description of problems in the previous case are matched. The similarities between them are calculated, and based on the solutions from similar previous cases, a new solution is reasoned and generated for the new case (Guo 2012). Case retrieval calculates the similarity between new and previous cases and the similarity of the two is the difference in value between cases. One object usually has three types of values, numerical, range and fuzzy values. Three types of values form six different similarity calculation problems. The formula for each similarity calculation problem is shown in Table 1.

Table 1: Formulae table counting the degree of similarity by the weighted average method

No.	Object	Similarity solution formula	Description
1	Numerical value of *X* and *Y*	$sim(x,y)=1-\frac{\lvert x-y\rvert}{\beta-\alpha}\quad x,y\in[\alpha,\beta]$	α, β are upper limit and lower limit of the x and y
2	Numerical and scope	$sim(\alpha,[b_1,b_2])=\frac{\int_{b_1}^{b_2} sim(\alpha,x)dx}{b_2-b_1}$	$sim(x,y)=1-\frac{\lvert x-y\rvert}{\beta-\alpha}$
3	Numerical value and fuzzy number	$sim(\alpha,X)=\frac{\int_{\alpha}^{\beta} X(x)sim(\alpha,x)dx}{\int_{\alpha}^{\beta} X(x)dx}\quad \max\{X(x)\}\quad x\in[\alpha,\beta]$	α, β are upper limit and lower limit of fuzzy number for $X(x)$
4	Values between interval	$sim([a_1,a_2],[b_1,b_2])=\frac{\int_{a_1}^{a_2}\int_{b_1}^{b_2} sim(x,y)dydx}{(a_2-a_1)(b_2-b_1)}$	
5	Interval and fuzzy number	$sim([a_1,a_2],X)=\frac{\int_{a_1}^{a_2}\int_{\alpha}^{\beta} sim(x,y)dydx}{(a_2-a_1)\int_{\alpha}^{\beta} X(x)dx}\quad \max\{X(x)\}$	
6	Fuzzy number X_a, X_b	$sim(X_a,X_b)=\frac{\int_{a}^{b}\int_{\alpha}^{\beta} X_a(\mathrm{x})X_a(y)sim(x,y)dydx}{\int_{\alpha}^{\beta} X_a(x)dx\int_{\alpha}^{\beta} X_b(x)dx}$	

RBR and CBR have been widely used in designing machinery systems, and many studies have assessed development of expert systems using RBR and CBR. In the field of mechanical design, an expert system to aid design of ship engine room automation was developed (Kowalski et al. 2005). Gao (2011) proposed a CBR method for machining fixture design and designed an integrated system for machining fixtures based on VR A case-based parametric system for testing turntables was designed and the system produced automatic and intelligent designs for turntables (Liu and Xi 2011). Li et al. (2012) built a CBR-Based CAD System for Subframe Design of Aerial Work Trucks and proposed a system framework and implementation method for a subframe CAD system based on CBR. Yang et al. (2004) designed a system for fault diagnosis of induction motors, an innovative approach to integrate CBR with Petri net in the field of fault diagnosis. Yang et al. (2012) developed a web-oriented expert system to save time in fault diagnosis of gear boxes and created an expert solution to achieve precise and quick maintenance.

As forestry machinery developers offer various types of products, it is difficult to choose the appropriate forestry machinery at the beginning of the model selection. Users need to know methods for fault diagnosis and maintenance of equipment. By collecting and analyzing mechanical information in different processes of forestry production, this study proposes a matching reasoning algorithm and a weight adjustment method. Based on the different stages of the production processes and integration of RBR with CBR, this study establishes an expert system of forestry machinery matching which is web-based. To increase knowledge processing ability and strengthen system maintainability, I used various mechanical matching processes in a unified generation network framework environment by network integration.

Materials and methods

Acquisition and representation of forestry machinery knowledge

The system describe here aims to integrate the mechanization processes for timber production separated into seven processes: timber felling, site preparation, cutting point, transport, planting, tending and harvesting. The system addresses machinery for

ditching, digging, tree-planting, felling, seedling-plugging, seedling-lifting, and traction. Knowledge induction accumulates information about these various types of machinery and is used in the process of machine-matching. Knowledge of machinery is categorized as quantitative parameters (CBR) and qualitative parameters (RBR).

RBR parameters were defined based on machine field applications such as production processes, machine types, and operation types. These RBR parameters define the mechanical case. After defining this case, we can analyze and match machinery according to the CBR parameters of user needs. Examples of CBR parameters are the felling machine and its maximum power and speed, the biggest skid trail of felling, net timber quality, tree length, width, and height, and cost and other related properties.

The mixed knowledge representation mode was adopted in the system as follows:

IF n_1 and n_2 and ⋯ n_n and (Max ($N(A,B_i)$)>ξ) THEN Case_i

In this formula, n_1 and n_2 and ⋯ n_n are CBR parameters, and $Max(N(A,B_i)>\xi$ indicates the similarity after matching with the RBR parameters. The CBR parameters for the system are shown in Table 2.

Table 3: CBR breeding process list structure and parameters

Case	Para. 1	Para. 2	Para. 3	Para. 4	Para. 5	Para. 6	Para. 7
Ditching machines	Trenching depth	Minimum width	Ditching power	Ditching efficiency	-	-	-
Digging machines	Digging diameter	Digging deep pit	Digging efficiency	Minimum power	Maximum gradient	Costing	-
Tree-planting machines	Maximum height	Seeding depth	Minimum power	Planting efficiency	Maximum gradient	—	-
Cutting machines	Maximum power	Maximum speed	Saw cut the tree diameter	Net mass	Size (L)	Size (W)	Size (H)
Seedling-plugging machines	Transplant depth	Minimum spacing	Maximum spacing	Power	-	-	-
Seedling-lifting machines	Operating width	Lifter depth	Minimum power	Lifter efficiency	-	-	-
Motivation traction machines	Maximum power	Maximum speed	Maximum load	-	-	-	-

Para.: parameter; "-": no parameters

Designing the knowledge base

Integration must be considered during when designing the knowledge base. In the knowledge storage procedure, the MySQL database was used and during the matching process, quantitative parameter names and the corresponding parameter properties, as well as weights generated in the process of parameter matching are stored separately in three knowledge tables.

These three tables were created as the 'pxjxcanshu' table, which was used to store parameter names during the matching process and can be called the "parameter table" for short. A 'pxjxshuming' table is used to store parameter properties during the matching process and can be called the "attributes list" for short. A 'pxjxquanzhi' table stores the corresponding weights of quantitative parameters during the matching process and can be called a "value table" for short. The three tables have the same structure and are used in framework integration in the reasoning process. A collective integration method is described later.

Designing mechanical-matching reasoning machines

RBR parameter matching

The RBR parameter matching process uses the method of forward reasoning to retrieve the entire knowledge base. It uses matching production rules which are composed of qualitative parameters for rules matching. According to the qualitative parameters, it is feasible to narrow the scope of knowledge in the knowledge base. The matching process is relatively simple. It is not describe here. The following is the quantitative matching process for the knowledge obtained after completion of the CBR parameter matching process.

CBR parameter matching

Parameterized cultivating machine characteristic vector: The quantitative parameters from case matching are stored in the knowledge base according to the different requirements of parameters. The quantitative parameter set is comprised of the cultivating machine's characteristic vector:

$$Y_i = \left(Y_{i1}, Y_{i2}, Y_{i3}, \cdots Y_{in}\right)^T \tag{1}$$

Y_{in} represents the values of different quantitative parameters. The design of quantitative parameters adopts the method of extreme value storage in the design process. Quantitative parameters which influence matching parameters are stored in the knowledge base as extreme values. For example specification of a digging machine is based on its application: the required maximum diameter and depth of the hole/trench, and the required maximum and minimum power. These matching parameters are stored. In a parametric process, n corresponds to the number of quantitative parameters in the knowledge base, so the range of n according to differences in cultivation machines. The different types of cultivation machinery i correspond to different types of matching processes. Each type of machinery includes m cultivation machinery matching feature vectors to yield a cultivation machinery matching feature vector space model:

$$Y_m = \begin{pmatrix} Y_{11} & Y_{12} & \cdots & Y_{1m} \\ Y_{21} & Y_{22} & \cdots & Y_{2m} \\ \vdots & \vdots & & \\ Y_{n1} & Y_{n2} & \cdots & Y_{nm} \end{pmatrix} \tag{2}$$

The parameterized matching machinery vector is based on the

varying parameter area of the cultivation machinery matching feature vector space. The quantitative parameters which can meet the demands of actual matching, a user inputs, can be expressed as:

$$X=\left(X_1,X_2,X_3,\cdots,X_n\right) \tag{3}$$

Its structure is the same as the corresponding matching feature of the cultivation machinery vector. The parameters provide the range from $Min(Y_{in})$ to $Max(Y_{in})$ for reference when the user input quota parameters.

Similarity calculation is the core step of the inference process. The similarity between X and Y_m are calculated according to the matching feature vector X, which is inputted by the user, and the cultivation machinery matching vector space in the case database. After calculating the similarity, a similarity vector is obtained: $(\varpi_1,\varpi_2,\ldots,\varpi_n)$, Max (ϖ_m) corresponds to m, the matching machinery. Firstly, the similarity calculation calculates the individual parameter similarity for different quota parameters. Then it calculates comprehensive similarity according to the defined weights. The individual parameter similarity is expressed through σ_{ij}:

$$SIM\left(X_j,Y_{ij}\right)=\sigma_{ij}=1-\frac{\left|X_j-Y_{ij}\right|}{\left|Max\left(Y_{ij}\right)-Min\left(Y_{ij}\right)\right|} \tag{4}$$

In this expression, X_j is the parameter input by a user, Y_{ij} is the parameter value of each matching case. First, the user gets the matching range according to $Max(Y_{ij})$ and $Min(Y_{ij})$. Then, the user inputs the quota parameter value which corresponds to the range, and finally he calculates the similarity between matching parameters and case parameters in the knowledge base. Matching vector X and vector space Y calculates the individual similarity as σ_{ij}, it generates individual similarity feature vector space:

$$\sigma=\begin{pmatrix}\sigma_{11} & \sigma_{12} & \cdots & \sigma_{1m}\\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2m}\\ \vdots & \vdots & & \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nm}\end{pmatrix} \tag{5}$$

After calculating the individual similarity, the system adopts an analytic hierarchy process (AHP). Thus, it makes the calculation of the overall similarity matching process. Each matching feature vector space Y of the cultivation machinery corresponds to each weight feature vector:

$$\beta_i=\left(\beta_{i1},\beta_{i2},\beta_{i3}\cdots\beta_{in}\right) \tag{6}$$

β_{ij} is the weight relationship between every quota parameter and the overall matching similarity, and it marks the importance degree of the target to the random case in its case space. If β_{ij}=0, it satisfies $\beta_{ij}\in[0,1]$, $\sum_{j=1}^{n}\beta_{ij}=1$. In this case, it indicates that the quota parameters have no effect to the whole matching process. The greater the value β_{ij}, the greater the effect of j on the overall matching process. The similarity calculation is obtained through the computation of matching machinery feature vector and every weighted distance of the cultivation machinery feature vector to determine the overall degree of similarity:

$$SIM\left(X,Y_i\right)=\sum_{j=1}^{n}\beta_{ij}\times SIM\left(X_j,Y_{ij}\right)=\varpi_i \tag{7}$$

The quota parameter's weight β_{ij} is saved in the knowledge base after being evaluated by the expert. After each matching process, the system provides a self-study function to adjust to the parameter weight. For example, sorting uses two methods: threshold value sorting and example number sorting. First, threshold value sorting sets the smallest threshold value δ for the similarity. The overall similarity obtained each time is a group of similarity coefficients. If $SIM(X,Y)>\delta$, the corresponding case serves as an inference result. Example number sorting first sets the case number n, and orders case numbers according to the whole similarity size. Here I use the threshold sorting method, first setting the threshold number δ=0.6, when $SIM(X,Y)>0.6$, then sorting the corresponding cases according to the overall similarity from large to small as the inference conclusion.

Weight adjustment method

According to expert experience, weight determination can be used to investigate and analyze different matching processes. Expert weight evaluation, which adopts the individual mean value method to identify the weighting value of parameters, is used as the system default weight stored in the 'pxjxquanzhi' table and the matching computation as the initialization value.

In the matching process, we established X_j = unknown, and it indicates that the matching factor cannot be determined in this matching process. The system will set σ_{ij}=1 as the default, in such a case we could consider that X_j has no effect in this matching process, which is the effect of the smallest factor. After every matching process, β_{ij} is adopted as the weight reducing factor if X_j = unknown. According to the reduced weight value of X_j, the other matching field makes corresponding increments to the weighted values.

In the system we establish η as the weight adjustment threshold effect value, i.e. if X_j = unknown then $\beta_{ij}=\beta_{ij}-\eta$, until $\beta_{ij}=0$ each time. The adjustment η increases to another weighted factor β_{ij} according to the most superior combination assigning value method of squared residuals.

$\sqrt{(\sigma_{i1}-\sigma_i)^2+\cdots+(\sigma_{im}-\sigma_i)^2}$ represents the residuals between the i^{th} quota parameter and the i^{th} parameter, which is the individual similarity of the overall machinery matching feature vector space. The value can reflect the dispersed degree between individual similarities. It is clear that the smaller value of dispersed degree plays a smaller role in the matching process. On the other hand, the larger value of dispersed degree plays a more

important role in the matching process. So we could use the ratio range,

which is $\sqrt{\left(\sigma_{i1}-\overline{\sigma_i}\right)^2+\cdots+\left(\sigma_{im}-\overline{\sigma_i}\right)^2}$

in $\sum_{i=1}^{n}\sqrt{\left(\sigma_{i1}-\overline{\sigma_i}\right)^2+\cdots+\left(\sigma_{im}-\overline{\sigma_i}\right)^2}$

to define a different parameter I's role in this matching process. That is, the parameter changes can reflect entire vector changes, so the following expression is used to make adjustment to β_i:

$$\beta_i=\beta_i+\frac{\sqrt{\left(\sigma_{i1}-\overline{\sigma_i}\right)^2+\cdots+\left(\sigma_{im}-\overline{\sigma_i}\right)^2}}{\sum_{i=1}^{n}\sqrt{\left(\sigma_{i1}-\overline{\sigma_i}\right)^2+\cdots+\left(\sigma_{im}-\overline{\sigma_i}\right)^2}}\eta \quad (8)$$

Every adjustment was made in the matching process according to each parameter's role, and thus $\beta_{ij}\in[0,1]$, $\sum_{j=1}^{n}\beta_{ij}=1$ pre-conditions are ensured. In the initial procedure, we set the datum of weight adjustment η=0.02 as the datum quantities.

System integration process

The purpose of the overall matching process is to integrate seven classes of forest mechanical matching systems where quantitative and qualitative parameters are of different types. Firstly, the integration process is defined by machinery quantitative parameters in the parameter table and this is used to retrieve the corresponding parameter entry which is defined in Table 1. Then we use the parameter sets to define the frame structure in a dynamic page and to retrieve the individual similarity calculation matching vector space according to the quantitative parameters of the attributes list. After a user inputs matching vectors, an individual similarity is calculated and then the corresponding weights are retrieved to calculate the overall similarity in the weight table. The detailed integration process is described in the following:

(1) After the selection of all qualitative parameters, a case set composed of a number of cases is obtained. The value of case set is stored in a two-dimensional array. The qualitative parameter name in the parameter table is retrieved to generate an array as Cs1[]. Using the number m of Cs1[] length matching qualitative parameters and using a m × 3 table generated by the FOR LOOP, the table of the reasoning integration pages is dynamically generated. The first column of the table contains the name of matching parameters generated by the array of Cs1[].

(2) In the second column of the table, a text box is dynamically generated through circular definition for the user's input goal actual parameters<input name="text <%=i%>"type="text" value="unknown">. In the third column of the table, each parameter of the maximum and minimum values are retrieved in the base case corresponding to minimum and maximum parameters as input information for user reference. If the user cannot determine the parameters or has no relevant parameter for the matching process, the user can enter the default unknown, the system will convert all input parameters and the similarity corresponding to the each case as 1.

(3) After all parameters have been entered, the individual similarity is first calculated according to the design of inference. The weight value is retrieved from the weight value table according to the fields in Cs1[] and the overall similarity is calculated.

(4) After calculating the overall similarity, the case which has similarity above 0.6 is selected in accordance with descending order of sorting for output. In the page, if the user is satisfied with the matching process then he can decide whether to adjust the weighting values in the matching process.

Results

Take the digging machine matching as an example of matching cases *Y* and matching machinery feature vector *X*, which feature vector is shown in Table 3.

Table 3: Experimental inputs of digging machine matching

Case	Para. 1	Para. 2	Para. 3	Para. 4	Para. 5	Para. 6	Results
Y_1	70	120	150	55	30	5000	3wh-60
Y_2	50	90	180	30	20	4000	3wh-50
Y_3	60	100	160	50	30	4500	WXJ50
Y_4	70	90	130	60	30	5000	WXJ60
Y_5	100	90	160	50	20	7500	WXJ80
X	50	95	170	50	-	-	

Para.: parameter; "-": no parameters

Quantitative parameters in the case base case matrix composition:

$$Y=\begin{pmatrix}70 & 50 & 60 & 70 & 100\\ 120 & 90 & 100 & 90 & 90\\ 150 & 180 & 160 & 130 & 160\\ 55 & 30 & 50 & 60 & 50\\ 30 & 20 & 30 & 30 & 20\\ 5000 & 4000 & 4500 & 5000 & 7500\end{pmatrix} \quad (9)$$

The user inputs feature vector *X*, and receives the input matching vector: *X*=(50 95 170 50 - -).

According to the formula (4), we calculate individual similarity of the each quantitative parameter between the input feature vector X and case vector space Y:

$$SIM\left(X_j,Y_{ij}\right)=\sigma_{ij}=\begin{pmatrix}0.60 & 1.00 & 0.80 & 0.60 & 0.00\\ 0.16 & 0.83 & 0.83 & 0.83 & 0.83\\ 0.60 & 0.80 & 0.80 & 0.20 & 0.80\\ 0.83 & 0.33 & 1.00 & 0.66 & 1.00\\ 1.00 & 1.00 & 1.00 & 1.00 & 1.00\\ 1.00 & 1.00 & 1.00 & 1.00 & 1.00\end{pmatrix} \quad (10)$$

According to expert evaluation, the corresponding weight value feature vector β=(0.2 0.2 0.2 0.2 0.05 0.05) calculates

ω=(0.538 0.692 0.786 0.558 0.626), the overall similarity. We can ensure that the threshold δ=0.6 is met. After sorting, the greatest similarity is Y_3. Finally, users decide if they are satisfied with this matching process and if they require adjustments to the weighting values. If the users are satisfied with the matching process, then we can adjust the assigned weights and set the value η=0.02. The system will set β_5=β_5-η=0.03 and β_6=β_6-η=0.03 according to X_5= unknown and X_6= unknown; According to expression (8) the residual weight values β_1=0.208; β_2=0.211; β_3=0.210; β_4=0.211 are adjusted. After the adjustment, β=(0.208 0.211 0.210 0.211 0.03 0.03) will be stored in the weight table.

Conclusion

By analyzing the forestry machinery in the production process, we established and realized an expert system of machinery selection and matching that integrates seven classes of forestry machinery and is based on network architecture. Therefore, we can systematically integrate the weight value adjusting method based on the sum of squared deviations. This enables adjustment of the weight value knowledge base in every matching process and more accurate and scientific representation of the matching process. In the realization process, we adopt the structure of open source framework for development. In this way, the calculation process can become more convenient and its practical value can be realized.

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